customer_segmentation_pdf

December 15, 2023

#

Credit Card Client Segmentation Project

1 Introduction

Understanding and catering to the diverse needs of credit cardholders is pivotal for a bank's success. To gain actionable insights into the behavior of approximately 9,000 active credit cardholders over the last six months, we embark on a strategic client segmentation project. This initiative aims to categorize and comprehend the distinct patterns and preferences exhibited by credit card users, enabling the bank to tailor its services to different client segments effectively.

The dataset at our disposal encapsulates a comprehensive snapshot of each cardholder's financial activity. With columns detailing balance, purchase behavior, credit limits, payment habits, and other critical metrics, we have a wealth of information to unravel. Our primary objective is to identify and delineate diverse client segments based on their credit card usage patterns. This segmentation will empower the bank to implement targeted strategies, optimizing customer satisfaction and financial outcomes.

Let's delve into the key columns that encapsulate the financial dynamics of our credit card users:

Column	Description
Cust_id	Describes the unique identification of the credit cardholder.
Balance	Indicates the amount of money left in the account for making purchases.
Balance_freq	Reflects how often the account balance is updated. Score ranges from 0 to 1(1 = frequently, 0 = not frequently).
Purchases	Represents the total amount spent on purchases from the account.
Oneoff_purchases	Denotes the maximum amount spent in a single purchase transaction.
Istallments_purchases	Indicates the amount spent on purchases paid in installments.
Cash_advance	Shows the cash in advance provided by the user.
Purchases_freq	Reflects how frequently purchases are made. Score ranges from 0 to 1(1 = frequently, 0 = not frequently).
Oneoff_purch_freq	Indicates how often one-time purchases occur. Score ranges from 0 to 1(1 = frequently, 0 = not frequently).
Purch_instmts_freq	Reflects how often purchases in installments are made. Score ranges from 0 to 1(1 = frequently, 0 = not frequently).
Cash_advance_freq	Indicates how frequently cash in advance is paid.
Cash_advance_trx	Represents the number of transactions made with "Cash in Advance."
Purchases_trx	Represents the number of purchase transactions made.

Column	Description
Credit_limit	Denotes the credit card limit assigned to the user.
Payments	Represents the total amount of payments made by the user.
Minimum_payments	Denotes the minimum amount of payments made by the user.
Prc_full_payment	Represents the percentage of the full credit card balance paid by the user.
Tenure	Represents the duration of credit card service for the user in months.

2 Import Dataset and packages

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter

# Preprocess
from sklearn.preprocessing import StandardScaler
from sklearn.impute import KNNImputer
from sklearn.decomposition import PCA

# Models
from sklearn.cluster import KMeans
from sklearn.cluster import DBSCAN
from sklearn.neighbors import NearestNeighbors

# Metrics
from sklearn.metrics import silhouette_score

# Hyperparametrization
from sklearn.model_selection import GridSearchCV

# Warnings
import warnings
warnings.filterwarnings("ignore")
```

[3]:
```
# Load dataset:

df = pd.read_csv("credit_card_data.csv")
```

[4]:
```
df_preprocess = df.copy()
```

3 Exploratory Data Analysis

[5]:
```
df_preprocess.head(3)
```

[5]:
```
  CUST_ID      BALANCE  BALANCE_FREQUENCY  PURCHASES  ONEOFF_PURCHASES  \
0  C10001    40.900749           0.818182      95.40              0.00
1  C10002  3202.467416           0.909091       0.00              0.00
2  C10003  2495.148862           1.000000     773.17            773.17

   INSTALLMENTS_PURCHASES  CASH_ADVANCE  PURCHASES_FREQUENCY  \
0                    95.4      0.000000             0.166667
1                     0.0   6442.945483             0.000000
2                     0.0      0.000000             1.000000

   ONEOFF_PURCHASES_FREQUENCY  PURCHASES_INSTALLMENTS_FREQUENCY  \
0                         0.0                          0.083333
1                         0.0                          0.000000
2                         1.0                          0.000000

   CASH_ADVANCE_FREQUENCY  CASH_ADVANCE_TRX  PURCHASES_TRX  CREDIT_LIMIT  \
0                    0.00                 0              2        1000.0
1                    0.25                 4              0        7000.0
2                    0.00                 0             12        7500.0

      PAYMENTS  MINIMUM_PAYMENTS  PRC_FULL_PAYMENT  TENURE
0   201.802084        139.509787          0.000000      12
1  4103.032597       1072.340217          0.222222      12
2   622.066742        627.284787          0.000000      12
```

We are going to convert the columns to lowercase for better processing:

[6]:
```
df_preprocess.columns = [col.lower() for col in df_preprocess.columns]
```

3.1 Column information

[7]:
```
df_preprocess.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   cust_id                           8950 non-null   object
 1   balance                           8950 non-null   float64
 2   balance_frequency                 8950 non-null   float64
 3   purchases                         8950 non-null   float64
 4   oneoff_purchases                  8950 non-null   float64
 5   installments_purchases            8950 non-null   float64
```

```
 6   cash_advance                        8950 non-null   float64
 7   purchases_frequency                 8950 non-null   float64
 8   oneoff_purchases_frequency          8950 non-null   float64
 9   purchases_installments_frequency    8950 non-null   float64
 10  cash_advance_frequency              8950 non-null   float64
 11  cash_advance_trx                    8950 non-null   int64
 12  purchases_trx                       8950 non-null   int64
 13  credit_limit                        8949 non-null   float64
 14  payments                            8950 non-null   float64
 15  minimum_payments                    8637 non-null   float64
 16  prc_full_payment                    8950 non-null   float64
 17  tenure                              8950 non-null   int64
dtypes: float64(14), int64(3), object(1)
memory usage: 1.2+ MB
```

[8]:
```
df_preprocess.groupby(by="tenure")["cust_id"].count()
```

[8]:
```
tenure
6      204
7      190
8      196
9      175
10     236
11     365
12    7584
Name: cust_id, dtype: int64
```

3.2 Column stats

[9]:
```
df_preprocess.describe().T
```

[9]:
```
                                  count         mean          std        min  \
balance                          8950.0  1564.474828  2081.531879   0.000000
balance_frequency                8950.0     0.877271     0.236904   0.000000
purchases                        8950.0  1003.204834  2136.634782   0.000000
oneoff_purchases                 8950.0   592.437371  1659.887917   0.000000
installments_purchases           8950.0   411.067645   904.338115   0.000000
cash_advance                     8950.0   978.871112  2097.163877   0.000000
purchases_frequency              8950.0     0.490351     0.401371   0.000000
oneoff_purchases_frequency       8950.0     0.202458     0.298336   0.000000
purchases_installments_frequency 8950.0     0.364437     0.397448   0.000000
cash_advance_frequency           8950.0     0.135144     0.200121   0.000000
cash_advance_trx                 8950.0     3.248827     6.824647   0.000000
purchases_trx                    8950.0    14.709832    24.857649   0.000000
credit_limit                     8949.0  4494.449450  3638.815725  50.000000
payments                         8950.0  1733.143852  2895.063757   0.000000
minimum_payments                 8637.0   864.206542  2372.446607   0.019163
prc_full_payment                 8950.0     0.153715     0.292499   0.000000
```

```
tenure                            8950.0    11.517318     1.338331   6.000000

                                          25%          50%          75%  \
balance                            128.281915   873.385231  2054.140036
balance_frequency                    0.888889     1.000000     1.000000
purchases                           39.635000   361.280000  1110.130000
oneoff_purchases                     0.000000    38.000000   577.405000
installments_purchases               0.000000    89.000000   468.637500
cash_advance                         0.000000     0.000000  1113.821139
purchases_frequency                  0.083333     0.500000     0.916667
oneoff_purchases_frequency           0.000000     0.083333     0.300000
purchases_installments_frequency     0.000000     0.166667     0.750000
cash_advance_frequency               0.000000     0.000000     0.222222
cash_advance_trx                     0.000000     0.000000     4.000000
purchases_trx                        1.000000     7.000000    17.000000
credit_limit                      1600.000000  3000.000000  6500.000000
payments                           383.276166   856.901546  1901.134317
minimum_payments                   169.123707   312.343947   825.485459
prc_full_payment                     0.000000     0.000000     0.142857
tenure                              12.000000    12.000000    12.000000

                                          max
balance                           19043.13856
balance_frequency                     1.00000
purchases                         49039.57000
oneoff_purchases                  40761.25000
installments_purchases            22500.00000
cash_advance                      47137.21176
purchases_frequency                   1.00000
oneoff_purchases_frequency            1.00000
purchases_installments_frequency      1.00000
cash_advance_frequency                1.50000
cash_advance_trx                    123.00000
purchases_trx                       358.00000
credit_limit                      30000.00000
payments                          50721.48336
minimum_payments                  76406.20752
prc_full_payment                      1.00000
tenure                               12.00000
```

3.3 NaN Values

[10]:
```
nan_values = df_preprocess.isna().sum()
percentages_nan = round(df_preprocess.isna().sum()*100/len(df_preprocess), 2)
df_nan_values = pd.DataFrame({'count': nan_values,'percentage':percentages_nan})
df_nan_values
```

[10]:

```
                                   count  percentage
cust_id                                0        0.00
balance                                0        0.00
balance_frequency                      0        0.00
purchases                              0        0.00
oneoff_purchases                       0        0.00
installments_purchases                 0        0.00
cash_advance                           0        0.00
purchases_frequency                    0        0.00
oneoff_purchases_frequency             0        0.00
purchases_installments_frequency       0        0.00
cash_advance_frequency                 0        0.00
cash_advance_trx                       0        0.00
purchases_trx                          0        0.00
credit_limit                           1        0.01
payments                               0        0.00
minimum_payments                     313        3.50
prc_full_payment                       0        0.00
tenure                                 0        0.00
```

Let's take a look at those NaN values:

- "credit_limit" Column

[11]:

```
df_preprocess[df_preprocess["credit_limit"].isna()]
```

[11]:

```
     cust_id    balance  balance_frequency  purchases  oneoff_purchases  \
5203  C15349  18.400472           0.166667        0.0               0.0

      installments_purchases  cash_advance  purchases_frequency  \
5203                     0.0    186.853063                  0.0

      oneoff_purchases_frequency  purchases_installments_frequency  \
5203                         0.0                               0.0

      cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
5203                0.166667                 1              0           NaN

      payments  minimum_payments  prc_full_payment  tenure
5203  9.040017         14.418723               0.0       6
```

- "minimum_payments" Column

[12]:

```
df_preprocess[df_preprocess["minimum_payments"].isna()]
```

[12]:

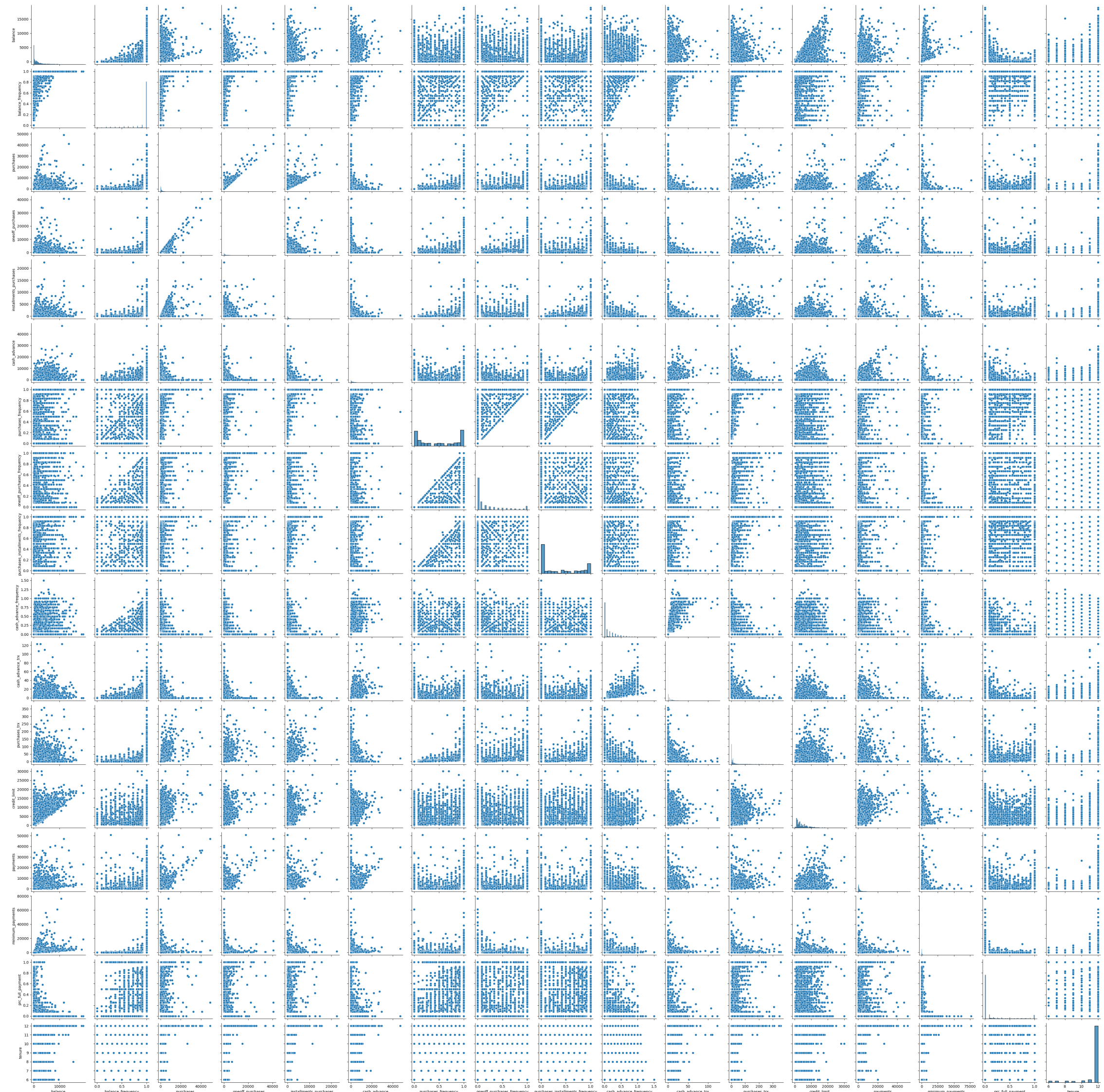
```
     cust_id      balance  balance_frequency  purchases  oneoff_purchases  \
3     C10004  1666.670542           0.636364    1499.00           1499.00
45    C10047  2242.311686           1.000000     437.00             97.00
47    C10049  3910.111237           1.000000       0.00              0.00
```

```
54    C10056     6.660517           0.636364     310.00             0.00
55    C10057  1311.995984           1.000000    1283.90          1283.90
…       …           …                 …          …                 …
8919  C19160    14.524779           0.333333     152.00           152.00
8929  C19170   371.527312           0.333333       0.00             0.00
8935  C19176   183.817004           1.000000     465.90             0.00
8944  C19185   193.571722           0.833333    1012.73          1012.73
8946  C19187    19.183215           1.000000     300.00             0.00

      installments_purchases  cash_advance  purchases_frequency  \
3                        0.0    205.788017             0.083333
45                     340.0    184.648692             0.333333
47                       0.0   1980.873201             0.000000
54                     310.0      0.000000             0.666667
55                       0.0      0.000000             0.250000
…                        …            …                  …
8919                     0.0      0.000000             0.333333
8929                     0.0   1465.407927             0.000000
8935                   465.9      0.000000             1.000000
8944                     0.0      0.000000             0.333333
8946                   300.0      0.000000             1.000000

      oneoff_purchases_frequency  purchases_installments_frequency  \
3                       0.083333                          0.000000
45                      0.083333                          0.333333
47                      0.000000                          0.000000
54                      0.000000                          0.666667
55                      0.250000                          0.000000
…                          …                                 …
8919                    0.333333                          0.000000
8929                    0.000000                          0.000000
8935                    0.000000                          0.833333
8944                    0.333333                          0.000000
8946                    0.000000                          0.833333

      cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
3                   0.083333                 1              1        7500.0
45                  0.166667                 2              5        2400.0
47                  0.500000                 7              0        4200.0
54                  0.000000                 0              8        1000.0
55                  0.000000                 0              6        6000.0
…                      …                    …              …             …
8919                0.000000                 0              2        1500.0
8929                0.166667                 5              0        1500.0
8935                0.000000                 0              6        1500.0
8944                0.000000                 0              2        4000.0
8946                0.000000                 0              6        1000.0
```

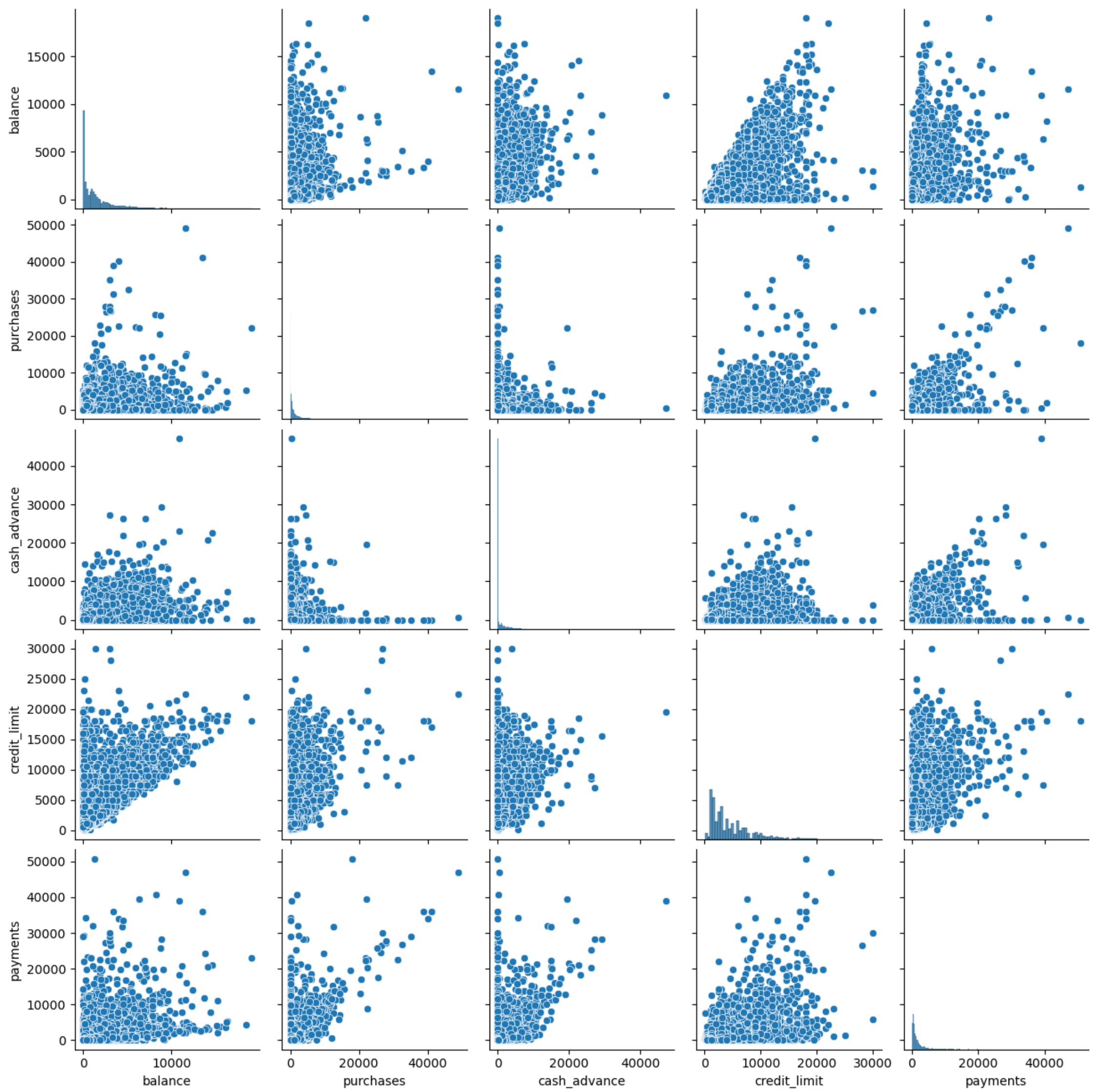
```
        payments  minimum_payments  prc_full_payment  tenure
3       0.000000               NaN               0.0      12
45      0.000000               NaN               0.0      12
47      0.000000               NaN               0.0      12
54    417.016763               NaN               0.0      12
55      0.000000               NaN               0.0      12
…          …                …                …      …
8919    0.000000               NaN               0.0       6
8929    0.000000               NaN               0.0       6
8935    0.000000               NaN               0.0       6
8944    0.000000               NaN               0.0       6
8946  275.861322               NaN               0.0       6

[313 rows x 18 columns]
```

3.4 Column correlation

[13]:
```
sns.pairplot(df_preprocess[["balance",
                            "balance_frequency",
                            "purchases",
                            "oneoff_purchases",
                            "installments_purchases",
                            "cash_advance",
                            "purchases_frequency",
                            "oneoff_purchases_frequency",
                            "purchases_installments_frequency",
                            "cash_advance_frequency",
                            "cash_advance_trx",
                            "purchases_trx",
                            "credit_limit",
                            "payments",
                            "minimum_payments",
                            "prc_full_payment",
                            "tenure"
                           ]]);
```



[14]:
```
sns.pairplot(df_preprocess[["balance",
                            "purchases",
                            "cash_advance",
                            "credit_limit",
                            "payments"
                           ]]);
```

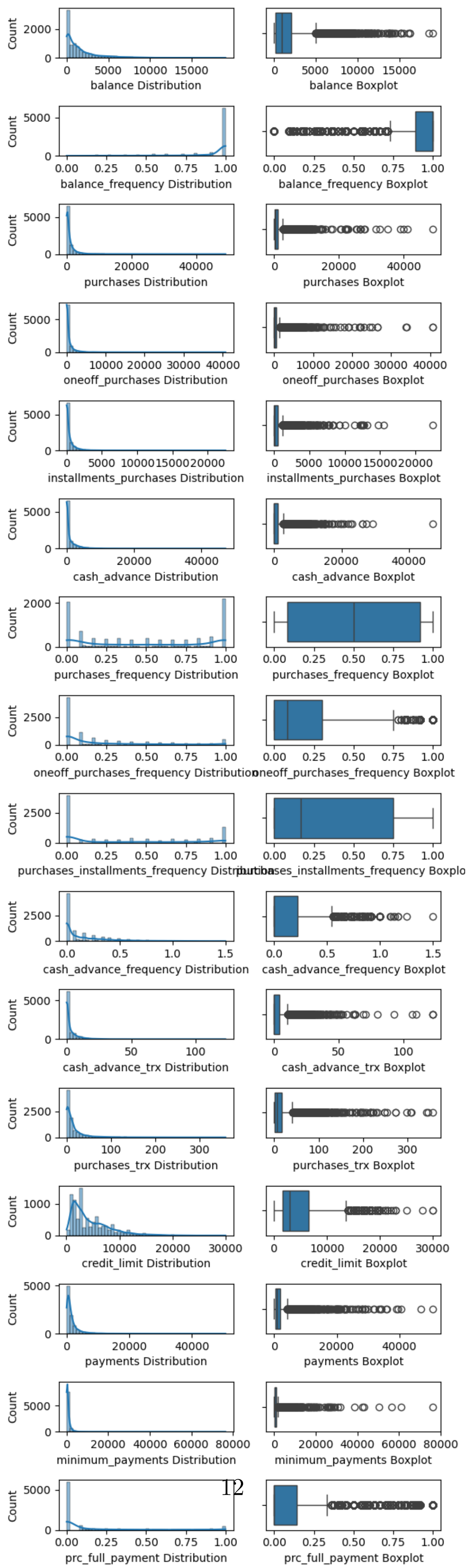


3.5 Column visualizations

Let's plot the distribution and a boxplot of each column:

[15]:
```
columns = df_preprocess.columns[1:-1]
rows = len(columns)

fig, axes =  plt.subplots(rows, 2, figsize = (6, 20))
axes = axes.flatten()
plot_num = [i for i in range(axes.size) if i%2 == 0]

for idx, col in zip(plot_num, columns):
    sns.histplot(x = df_preprocess[col], bins = 50, kde = True, ax = axes[idx])
```

```python
    axes[idx].set_xlabel(f'{col} Distribution')
    sns.boxplot(x = df_preprocess[col], ax = axes[idx + 1])
    axes[idx + 1].set_xlabel(f'{col} Boxplot')

plt.tight_layout()
plt.show()
```


Count
balance Distribution
balance Boxplot
balance_frequency Distribution
balance_frequency Boxplot
purchases Distribution
purchases Boxplot
oneoff_purchases Distribution
oneoff_purchases Boxplot
installments_purchases Distribution
installments_purchases Boxplot
cash_advance Distribution
cash_advance Boxplot
purchases_frequency Distribution
purchases_frequency Boxplot
oneoff_purchases_frequency Distribution
oneoff_purchases_frequency Boxplot
purchases_installments_frequency Distribution
purchases_installments_frequency Boxplo
cash_advance_frequency Distribution
cash_advance_frequency Boxplot
cash_advance_trx Distribution
cash_advance_trx Boxplot
purchases_trx Distribution
purchases_trx Boxplot
credit_limit Distribution
credit_limit Boxplot
payments Distribution
payments Boxplot
minimum_payments Distribution
minimum_payments Boxplot
prc_full_payment Distribution
prc_full_payment Boxplot

We can observe inconsistent values in the ‘cash_advance_frequency’ column that exceed 1. Let’s take a look at this column:

[16]:
```
df_preprocess[df_preprocess["cash_advance_frequency"] > 1]
```

[16]:
```
     cust_id      balance  balance_frequency  purchases  oneoff_purchases  \
681   C10708  5656.069801           1.000000     362.36            362.36
1626  C11680  2876.009336           1.000000     152.61            152.61
2555  C12629  5906.184924           1.000000     141.80            141.80
2608  C12684  7801.511533           1.000000     231.40            231.40
3038  C13127  3846.742530           1.000000       0.00              0.00
3253  C13347  5709.486507           0.833333       0.00              0.00
8055  C18273  1917.895730           1.000000     285.07            285.07
8365  C18588  3857.562230           1.000000       0.00              0.00

      installments_purchases  cash_advance  purchases_frequency  \
681                      0.0   7240.433194             0.250000
1626                     0.0   3719.650168             0.333333
2555                     0.0   1651.286918             0.125000
2608                     0.0   4109.465221             0.100000
3038                     0.0   1932.460679             0.000000
3253                     0.0   2794.326341             0.000000
8055                     0.0   6084.858872             0.363636
8365                     0.0   2127.213754             0.000000

      oneoff_purchases_frequency  purchases_installments_frequency  \
681                     0.250000                               0.0
1626                    0.333333                               0.0
2555                    0.125000                               0.0
2608                    0.100000                               0.0
3038                    0.000000                               0.0
3253                    0.000000                               0.0
8055                    0.363636                               0.0
8365                    0.000000                               0.0

      cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
681                 1.250000                12              2        8000.0
1626                1.166667                24              2        4000.0
2555                1.125000                12              2       10000.0
2608                1.100000                20              3       13500.0
3038                1.500000                18              0        5600.0
3253                1.166667                10              0        6000.0
8055                1.090909                28              6        3000.0
8365                1.142857                26              0        5000.0
```

```
         payments  minimum_payments  prc_full_payment  tenure
681    683.421497       2036.877611               0.0       8
1626   248.342971        584.926336               0.0       6
2555   933.969974        919.289675               0.0       8
2608  1593.617739       1522.496755               0.0      10
3038   496.245836        538.346874               0.0       6
3253   550.513331       1299.463370               0.0       6
8055  5692.682993        556.449635               0.0      11
8365   617.508991        538.396872               0.0       7
```

After analyzing the information and the graphs, it's considered to perform the following transformations on the values of our columns:

1. Cleaning the 'cash_advance_frequency' column, we found values above 1. These values will be set as NaN.

2. Logarithmic scaling transformation of the columns for handling outliers:

- "balance"
- "purchases"
- "oneoff_purchases"
- "installments_purchases"
- "cash_advance"
- "cash_advance_trx"
- "purchases_trx"
- "credit_limit"
- "payments"
- "minimum_payments"

3. Handling NaN values with KNN Imputer.

4 Data cleaning

4.1 Handling inconsistent values

[17]:
```
indices_inco = df_preprocess[df_preprocess["cash_advance_frequency"] > 1].index
```

[18]:
```
for indice in indices_inco:
    df_preprocess.loc[indice, "cash_advance_frequency"] = np.nan
```

[19]:
```
df_preprocess[df_preprocess["cash_advance_frequency"] > 1]
```

[19]:
```
Empty DataFrame
Columns: [cust_id, balance, balance_frequency, purchases, oneoff_purchases,
installments_purchases, cash_advance, purchases_frequency,
oneoff_purchases_frequency, purchases_installments_frequency,
cash_advance_frequency, cash_advance_trx, purchases_trx, credit_limit, payments,
```

```
minimum_payments, prc_full_payment, tenure]
Index: []
```

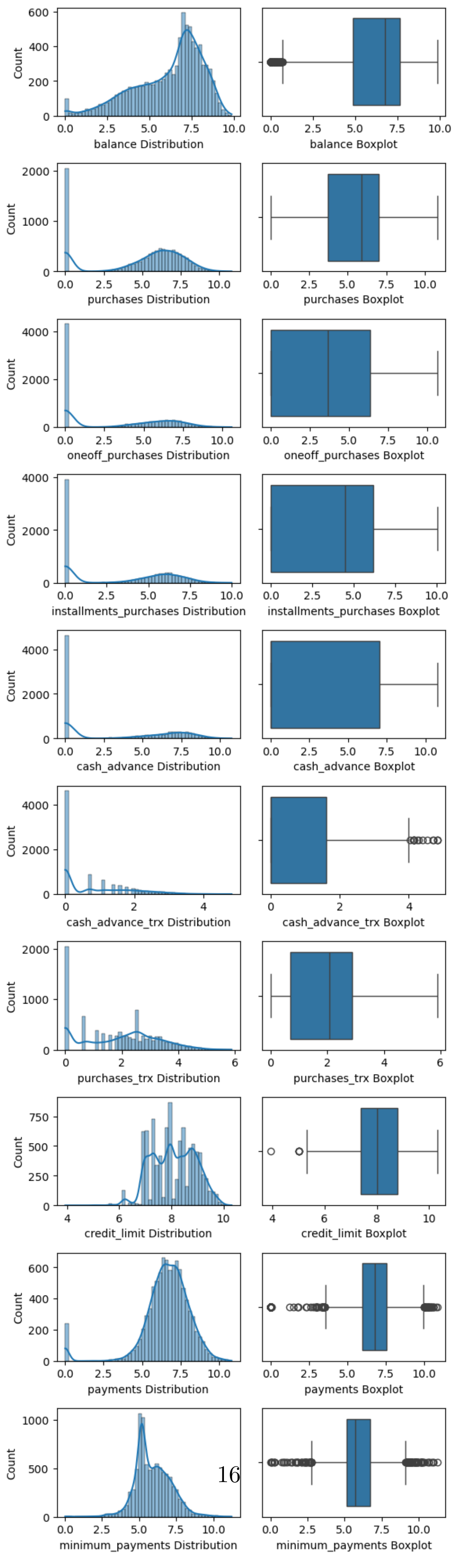
4.2 Outliers

For the treatment of outliers, we will logarithmically scale variables with high dispersion:

[20]:
```python
df_preprocess_log = df_preprocess.copy()

log_columns = ["balance", "purchases", "oneoff_purchases",␣
 ↪"installments_purchases", "cash_advance", "cash_advance_trx",␣
 ↪"purchases_trx", "credit_limit", "payments", "minimum_payments"]

for col in log_columns:
    df_preprocess_log[col] = df_preprocess_log[col].apply(lambda x: np.log(x+1))
```

Let's plot the distribution of each column:

[21]:
```python
rows = len(log_columns)

fig, axes =  plt.subplots(rows, 2, figsize = (6, 20))
axes = axes.flatten()
plot_num = [i for i in range(axes.size) if i%2 == 0]

for idx, col in zip(plot_num, log_columns):
    sns.histplot(x = df_preprocess_log[col], bins = 50, kde = True, ax =␣
 ↪axes[idx])
    axes[idx].set_xlabel(f'{col} Distribution')
    sns.boxplot(x = df_preprocess_log[col], ax = axes[idx + 1])
    axes[idx + 1].set_xlabel(f'{col} Boxplot')

plt.tight_layout()
plt.show()
```


balance Distribution
balance Boxplot
purchases Distribution
purchases Boxplot
oneoff_purchases Distribution
oneoff_purchases Boxplot
installments_purchases Distribution
installments_purchases Boxplot
cash_advance Distribution
cash_advance Boxplot
cash_advance_trx Distribution
cash_advance_trx Boxplot
purchases_trx Distribution
purchases_trx Boxplot
credit_limit Distribution
credit_limit Boxplot
payments Distribution
payments Boxplot
minimum_payments Distribution
minimum_payments Boxplot

[22]:
```python
def outliers(variable):
    '''
    Function to obtain the upper and lower limits after calculating the␣
 ↪interquartile range.
    '''
    Q1 = variable.quantile(q = 0.25)
    Q3 = variable.quantile(q = 0.75)

    # Rango intercuartil (IQR)
    IQR = Q3 - Q1

    # Calcular los limites inferior y superior
    lim_inf = Q1 - 1.5 * IQR
    lim_sup = Q3 + 1.5 * IQR

    return lim_inf, lim_sup
```

-

[23]:
```python
lim_inf_0, lim_sup_0 = outliers(df_preprocess_log["balance"])
percentage_outliers_balance =␣
 ↪len(df_preprocess_log[(~df_preprocess_log["balance"].between(lim_inf_0,␣
 ↪lim_sup_0))])*100/len(df_preprocess_log)

print(f"Lower limit: {lim_inf_0}\nUpper limit: {lim_sup_0}")
print(f"\nPercentage of outliers in the 'balance' column:␣
 ↪{round(percentage_outliers_balance, 2)} %")
```

```
Lower limit: 0.7128394793291024
Upper limit: 11.77725511104541

Percentage of outliers in the 'balance' column: 1.47 %
```

-

[24]:
```python
lim_inf_1, lim_sup_1 = outliers(df_preprocess_log["cash_advance_trx"])
percentage_outliers_cash_advance_trx =␣
 ↪len(df_preprocess_log[(~df_preprocess_log["cash_advance_trx"].
 ↪between(lim_inf_1, lim_sup_1))])*100/len(df_preprocess_log)

print(f"Lower limit: {lim_inf_1}\nUpper limit: {lim_sup_1}")
```

```
print(f"\nPercentage of outliers in the 'cash_advance_trx' column:␣
↪{round(percentage_outliers_cash_advance_trx, 2)} %")
```

```
Lower limit: -2.4141568686511503
Upper limit: 4.023594781085251

Percentage of outliers in the 'cash_advance_trx' column: 0.17 %
```

-

[25]:
```
lim_inf_2, lim_sup_2 = outliers(df_preprocess_log["credit_limit"])
percentage_outliers_credit_limit =␣
↪len(df_preprocess_log[(~df_preprocess_log["credit_limit"].between(lim_inf_2,␣
↪lim_sup_2))])*100/len(df_preprocess_log)

print(f"Lower limit: {lim_inf_2}\nUpper limit: {lim_sup_2}")
print(f"\nPercentage of outliers in the 'credit_limit' column:␣
↪{round(percentage_outliers_credit_limit, 2)} %")
```

```
Lower limit: 5.276392347185082
Upper limit: 10.8817026560161

Percentage of outliers in the 'credit_limit' column: 0.08 %
```

-

[26]:
```
lim_inf_3, lim_sup_3 = outliers(df_preprocess_log["payments"])
percentage_outliers_payments =␣
↪len(df_preprocess_log[(~df_preprocess_log["payments"].between(lim_inf_3,␣
↪lim_sup_3))])*100/len(df_preprocess_log)

print(f"Lower limit: {lim_inf_3}\nUpper limit: {lim_sup_3}")
print(f"\nPercentage of outliers in the 'payments' column:␣
↪{round(percentage_outliers_payments, 2)} %")
```

```
Lower limit: 3.552305914975821
Upper limit: 9.949787411950464

Percentage of outliers in the 'payments' column: 3.55 %
```

•

[27]:
```
lim_inf_4, lim_sup_4 = outliers(df_preprocess_log["minimum_payments"])
percentage_outliers_minimum_payments =␣
 ↪len(df_preprocess_log[(~df_preprocess_log["minimum_payments"].
 ↪between(lim_inf_4, lim_sup_4))])*100/len(df_preprocess_log)

print(f"Lower limit: {lim_inf_4}\nUpper limit: {lim_sup_4}")
print(f"\nPercentage of outliers in the 'minimum_payments' column:␣
 ↪{round(percentage_outliers_minimum_payments, 2)} %")
```

```
Lower limit: 2.765541166162284
Upper limit: 9.08816701812645

Percentage of outliers in the 'minimum_payments' column: 5.11 %
```

Removal of outliers in columns with a lower percentage of outliers.

[28]:
```
# "balance" Column
df_preprocess_log = df_preprocess_log[df_preprocess_log["balance"].
 ↪between(lim_inf_0, lim_sup_0)]

# "cash_advance_trx" Column
df_preprocess_log = df_preprocess_log[df_preprocess_log["cash_advance_trx"].
 ↪between(lim_inf_1, lim_sup_1)]

# "credit_limit" Column
df_preprocess_log = df_preprocess_log[df_preprocess_log["credit_limit"].
 ↪between(lim_inf_2, lim_sup_2)]
```

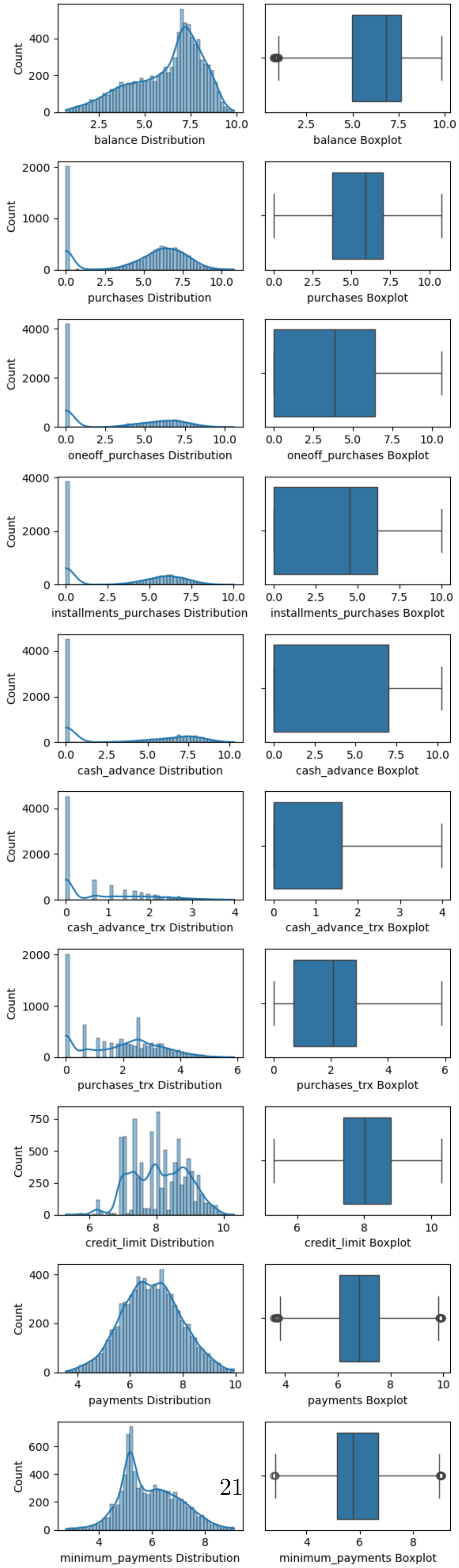
Handling outliers for columns with a higher percentage of outliers. We will set all values above and below the limits to NaN, and we will impute them using KNNImputer.

[29]:
```
# "payments" Column
indices_outliers_payments = df_preprocess_log[~(df_preprocess_log["payments"].
 ↪between(lim_inf_3, lim_sup_3))].index

for indice in indices_outliers_payments:
    df_preprocess_log.loc[indice, "payments"] = np.nan

# "minimum_payments" Column
indices_outliers_minimum_payments =␣
 ↪df_preprocess_log[~(df_preprocess_log["minimum_payments"].between(lim_inf_4,␣
 ↪lim_sup_4))].index
```

```
for indice in indices_outliers_minimum_payments:
    df_preprocess_log.loc[indice, "minimum_payments"] = np.nan
```

[30]:

```
fig, axes =  plt.subplots(rows, 2, figsize = (6, 20))
axes = axes.flatten()
plot_num = [i for i in range(axes.size) if i%2 == 0]

for idx, col in zip(plot_num, log_columns):
    sns.histplot(x = df_preprocess_log[col], bins = 50, kde = True, ax =␣
 ↪axes[idx])
    axes[idx].set_xlabel(f'{col} Distribution')
    sns.boxplot(x = df_preprocess_log[col], ax = axes[idx + 1])
    axes[idx + 1].set_xlabel(f'{col} Boxplot')

plt.tight_layout()
plt.show()
```


Count
balance Distribution
balance Boxplot
purchases Distribution
purchases Boxplot
oneoff_purchases Distribution
oneoff_purchases Boxplot
installments_purchases Distribution
installments_purchases Boxplot
cash_advance Distribution
cash_advance Boxplot
cash_advance_trx Distribution
cash_advance_trx Boxplot
purchases_trx Distribution
purchases_trx Boxplot
credit_limit Distribution
credit_limit Boxplot
payments Distribution
payments Boxplot
minimum_payments Distribution
minimum_payments Boxplot

5 Remove duplicates

[31]:
```
df_preprocess_log.duplicated().sum()
```

[31]:
```
0
```

6 Feature Engineering

[32]:
```
df_process_total = df_preprocess_log.copy()
```

6.1 Data selection

For our analysis, we will not consider the columns 'cust_id' and 'tenure'.

[33]:
```
df_preprocess_log = df_preprocess_log.drop(["cust_id", "tenure"], axis = 1)
```

[34]:
```
df_preprocess_log.head(3)
```

[34]:
```
    balance  balance_frequency  purchases  oneoff_purchases  \
0  3.735304           0.818182   4.568506          0.000000   
1  8.071989           0.909091   0.000000          0.000000   
2  7.822504           1.000000   6.651791          6.651791   

   installments_purchases  cash_advance  purchases_frequency  \
0                4.568506      0.000000             0.166667   
1                0.000000      8.770896             0.000000   
2                0.000000      0.000000             1.000000   

   oneoff_purchases_frequency  purchases_installments_frequency  \
0                         0.0                          0.083333   
1                         0.0                          0.000000   
2                         1.0                          0.000000   

   cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
0                    0.00          0.000000       1.098612      6.908755   
1                    0.25          1.609438       0.000000      8.853808   
2                    0.00          0.000000       2.564949      8.922792   

   payments  minimum_payments  prc_full_payment  
0  5.312231          4.945277          0.000000  
1  8.319725          6.978531          0.222222  
2  6.434654          6.442994          0.000000  
```

6.2 Missing values

For handling NaN values, we will use the KNN Imputer:

[35]:
```
nan_imputer = KNNImputer()
df_preprocess_log = pd.DataFrame(data = nan_imputer.
 ↪fit_transform(df_preprocess_log), columns = df_preprocess_log.columns)
df_preprocess_log.isna().sum()
```

[35]:
```
balance                             0
balance_frequency                   0
purchases                           0
oneoff_purchases                    0
installments_purchases              0
cash_advance                        0
purchases_frequency                 0
oneoff_purchases_frequency          0
purchases_installments_frequency    0
cash_advance_frequency              0
cash_advance_trx                    0
purchases_trx                       0
credit_limit                        0
payments                            0
minimum_payments                    0
prc_full_payment                    0
dtype: int64
```

7 Data enconding

We will use two dataframes for modeling, one with logarithmic scaling and another without scaling, comparing the results from both and choose the one that provides more coherent conclusions.

We'll scale the data using StandardScaler.

[36]:
```
# Datos en escala logarítmica:
df_processed_log = df_preprocess_log.copy()

scaler_log = StandardScaler()
df_processed_log_scaled = scaler_log.fit_transform(df_processed_log)
```

[37]:
```
# Datos sin escala:
df_processed = df_processed_log.copy()

for col in log_columns:
    df_processed[col] = df_processed[col].apply(lambda x: np.exp(x) - 1)

scaler = StandardScaler()
df_processed_scaled = scaler.fit_transform(df_processed)
```

8 Model

We will test the DBSCAN and K-Means Clustering models to determine the different types of customers.

Because the data distribution is not symmetric, we will evaluate the models with the logarithmic transformation, then check without scaling, and choose the most coherent results.

[37]:
```
def kmeans_inertia(k, X):
        '''
    Fits a KMeans model for different values of k.
    Calculates an inertia score for each k value.

    Args:
        k: (list of ints) - The different k values to try
        X: (array) - The training data

    Returns:
        inertia: (list) - A list of inertia scores, one for each value of k
    '''

        inertia = []

        for i in k:
            kms = KMeans(n_clusters = i, random_state = 42)
            kms.fit(X)
            inertia.append(kms.inertia_)

        return inertia

def kmeans_sil(k, X):
    '''
    Fits a KMeans model for different values of k.
    Calculates a silhouette score for each k value

    Args:
        k: (list of ints) - The different k values to try
        X: (array) - The training data

    Returns:
        sil_scores: (list) - A list of silhouette scores, one for each value of␣
 ↪k
    '''

    sil_scores = []

    for i in k:
        kms = KMeans(n_clusters = i, random_state = 42)
```

```
        kms.fit(X)
        sil_scores.append(silhouette_score(X, kms.labels_))

    return sil_scores
```

8.1 DBSCAN

DBSCAN is a density-based algorithm. These algorithms identify regions of high density that separate the data and create asymmetric clusters. They can find clusters of arbitrary shapes without being affected by noise.

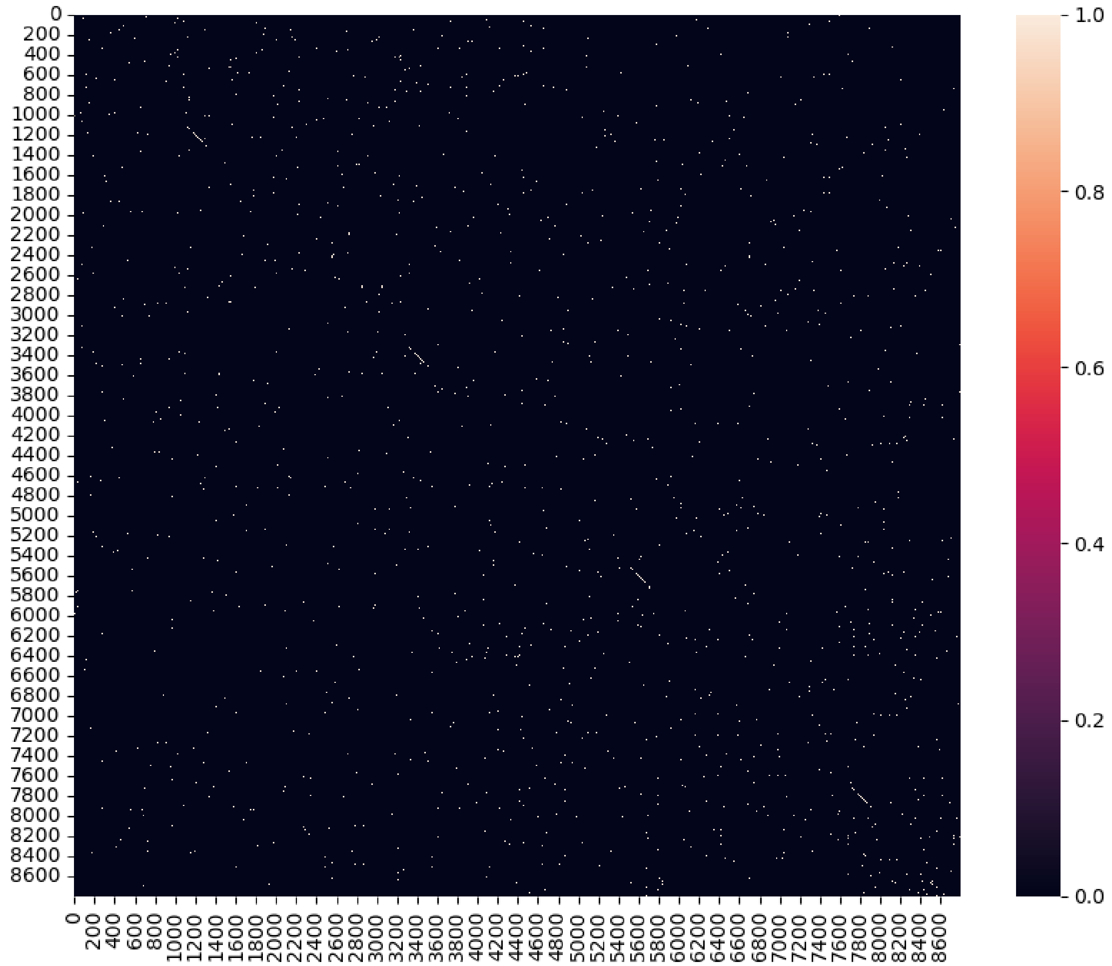
8.1.1 Hyperparametrization

We will model with the data in logarithmic scaling and without scaling, choosing the one that yields a more coherent result.

Let's start by using the elbow method on each case to obtain the optimal value for epsilon (eps).

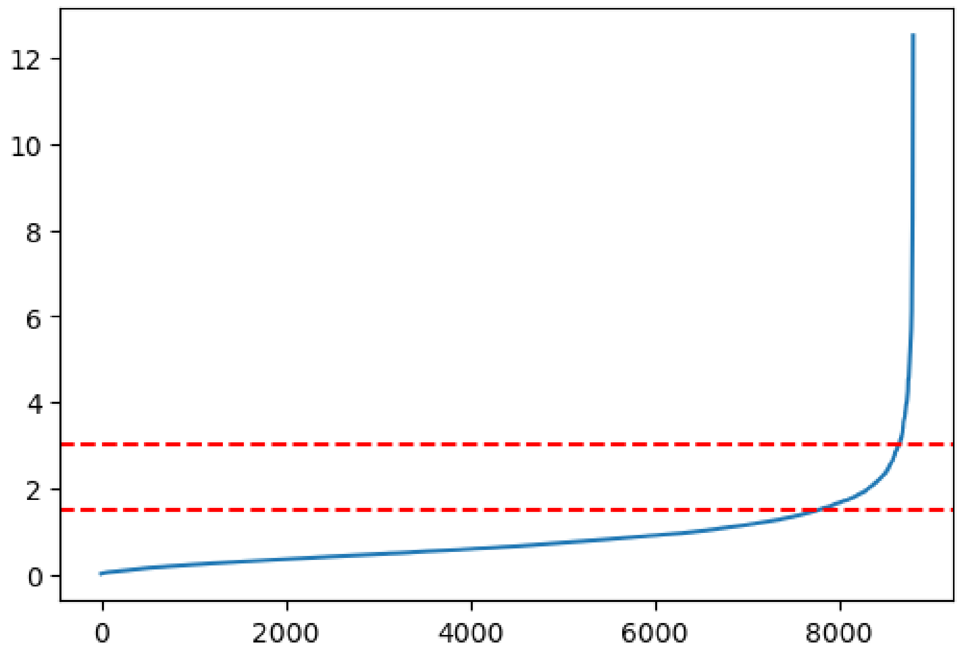
- Without Log Scaled:

[38]:
```
# Elbow method for DBSCAN

neigh = NearestNeighbors(n_neighbors = 2*df_processed_scaled.shape[1] - 1)
neigh.fit(df_processed_scaled)
distances, indices = neigh.kneighbors(df_processed_scaled)

# Distance plot with k-nearest neighbors
plt.figure(figsize = (10, 8))
sns.heatmap(neigh.kneighbors_graph(df_processed_scaled).toarray())

plt.show()
```



[39]:

```
# Plot to find the 'optimal' value of eps
plt.figure(figsize = (6, 4))
plt.plot(np.sort(distances, axis = 0)[:, 1])
plt.axhline(y= 1.5, color='red', linestyle='--')
plt.axhline(y= 3, color='red', linestyle='--')
plt.show()
```



[40]:
```
dbscan_params = []
num_columns = 2*df_processed_scaled.shape[1]
```

[41]:
```
%%time
for eps in [i/10 for i in range(15,30)]:
    for min_samples in [5, 10, num_columns]:
        for metric in ["cityblock", "cosine", "euclidean", "l1", "l2",␣
↪"manhattan"]:

            # DBSCAN
            model_DBSCAN = DBSCAN(eps = eps, min_samples = min_samples, metric␣
↪= metric)
            model_DBSCAN.fit(df_processed_scaled)

            # Clusters
            n_clusters = (len(set(model_DBSCAN.labels_)) - 1) # DBSCAN label␣
↪ouliers as Cluster_-1

            # Score
            try:
                sil_score = silhouette_score(X = df_processed_scaled, labels =␣
↪model_DBSCAN.labels_)
            except:
                silscore = np.nan
```

```
            dbscan_params.append([eps, min_samples, metric, sil_score,␣
↪n_clusters])
```

```
CPU times: total: 17min 10s
Wall time: 6min 20s
```

[42]:
```
df_dbscan_params = pd.DataFrame(dbscan_params, columns= ["eps", "min_samples",␣
↪"metric", "sil_score", "n_clusters"])
df_dbscan_params.sort_values(by="sil_score", ascending=False).head(3)
```

[42]:

	eps	min_samples	metric	sil_score	n_clusters
254	2.9	5	euclidean	0.598814	1
256	2.9	5	12	0.598814	1
260	2.9	10	euclidean	0.586331	1

[43]:
```
df_dbscan_params[df_dbscan_params["n_clusters"] == 3].
↪sort_values(by="sil_score", ascending=False).head(3)
```

[43]:

	eps	min_samples	metric	sil_score	n_clusters
2	1.5	5	euclidean	0.076852	3
4	1.5	5	12	0.076852	3
60	1.8	10	cityblock	0.015075	3

[44]:
```
model_DBSCAN = DBSCAN(eps = 1.5, min_samples = 5, metric = "euclidean")
model_DBSCAN.fit(df_processed_scaled)
```

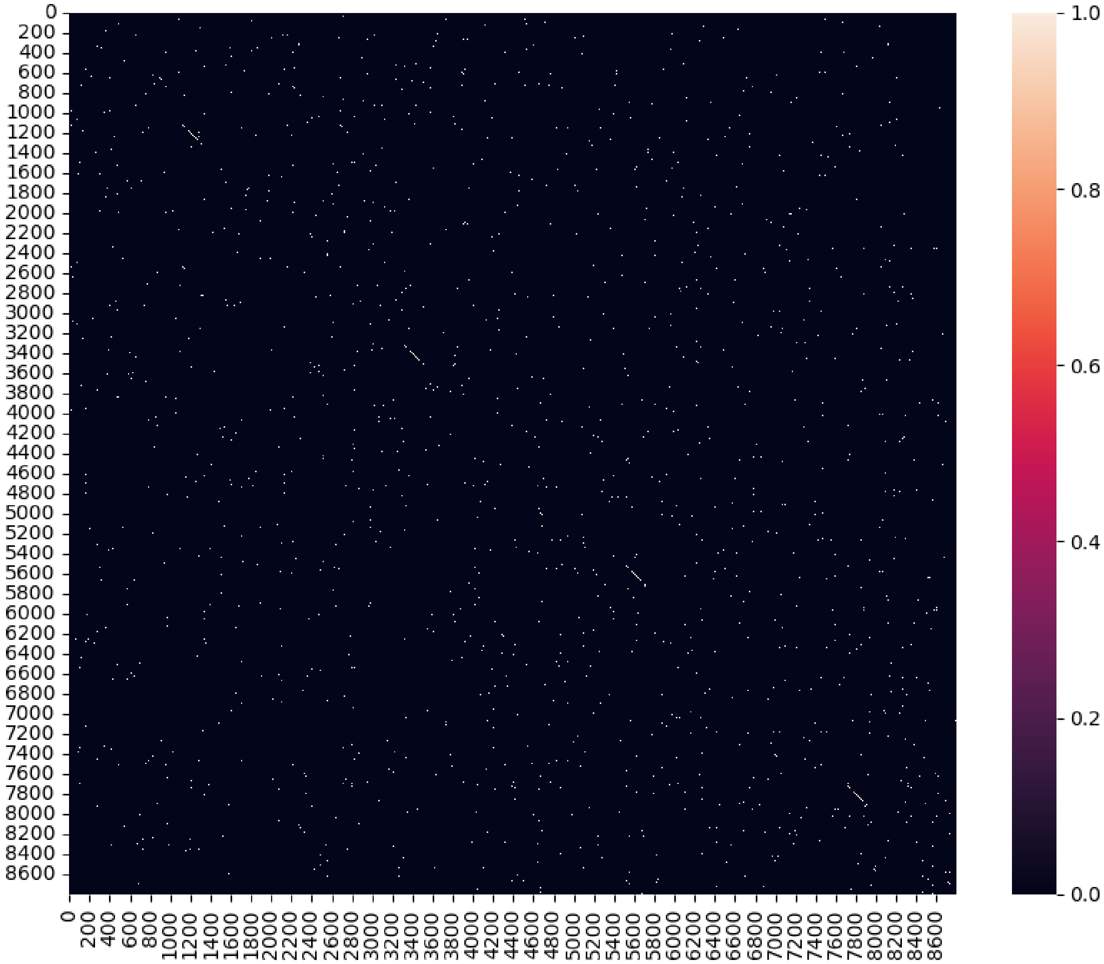
[44]:
```
DBSCAN(eps=1.5)
```

[45]:
```
Counter(model_DBSCAN.labels_)
```

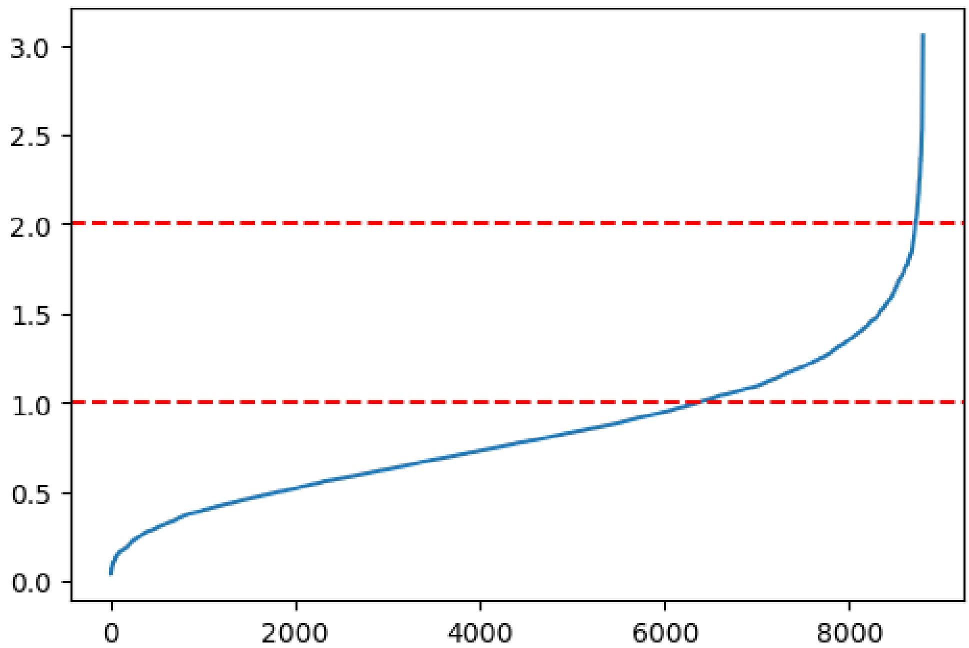
[45]:
```
Counter({0: 7510, -1: 1275, 1: 6, 2: 5})
```

- With Log Scaled:

[56]:
```
# Elbow method for DBSCAN

neigh_log = NearestNeighbors(n_neighbors = 2*df_processed_log_scaled.shape[1] -␣
↪1)
neigh_log.fit(df_processed_log_scaled)
distances_log, indices_log = neigh_log.kneighbors(df_processed_log_scaled)

# Distance plot with k-nearest neighbors
plt.figure(figsize = (10, 8))
sns.heatmap(neigh_log.kneighbors_graph(df_processed_log_scaled).toarray())

plt.show()
```



[57]:
```
# Plot to find the 'optimal' value of eps
plt.figure(figsize = (6, 4))
plt.plot(np.sort(distances_log, axis = 0)[:, 1])
plt.axhline(y= 1, color='red', linestyle='--')
plt.axhline(y= 2, color='red', linestyle='--')
plt.show()
```



[46]:
```
dbscan_params_log = []
num_columns = 2*df_processed_log_scaled.shape[1]
```

[48]:
```
%%time
for eps in [i/10 for i in range(10,20)]:
    for min_samples in [5, 10, num_columns]:
        for metric in ["cityblock", "cosine", "euclidean", "l1", "l2",␣
↪"manhattan"]:

            # DBSCAN
            model_DBSCAN_log = DBSCAN(eps = eps, min_samples = min_samples,␣
↪metric = metric)
            model_DBSCAN_log.fit(df_processed_log_scaled)

            # Clusters
            n_clusters = (len(set(model_DBSCAN_log.labels_)) - 1) # DBSCAN␣
↪label ouliers as Cluster_-1

            # Score
            try:
                sil_score = silhouette_score(X = df_processed_log_scaled,␣
↪labels = model_DBSCAN_log.labels_)
            except:
                silscore = np.nan
```

```
            dbscan_params_log.append([eps, min_samples, metric, sil_score,␣
↪n_clusters])
```

```
CPU times: total: 10min 34s
Wall time: 3min 51s
```

[49]:
```
df_dbscan_params_log = pd.DataFrame(dbscan_params_log, columns= ["eps",␣
↪"min_samples", "metric", "sil_score", "n_clusters"])
df_dbscan_params_log.sort_values(by="sil_score", ascending=False).head(3)
```

[49]:

	eps	min_samples	metric	sil_score	n_clusters
176	1.9	32	euclidean	0.120662	1
178	1.9	32	l2	0.120662	1
170	1.9	10	euclidean	0.120364	1

[53]:
```
df_dbscan_params_log[df_dbscan_params_log["n_clusters"] == 3].
↪sort_values(by="sil_score", ascending=False).head(3)
```

[53]:

	eps	min_samples	metric	sil_score	n_clusters
146	1.8	5	euclidean	0.026153	3
148	1.8	5	l2	0.026153	3
14	1.0	32	euclidean	-0.062267	3

[54]:
```
dbscan_log = DBSCAN(eps = 1.8, min_samples = 5, metric = "euclidean")
dbscan_log.fit(df_processed_log_scaled)
```

[54]:
```
DBSCAN(eps=1.8)
```

[55]:
```
Counter(dbscan_log.labels_)
```

[55]:
```
Counter({0: 8536, -1: 244, 2: 13, 1: 3})
```

8.1.2 Results

After analyzing the results obtained in both cases, we observe that in neither of them a coherent number of clusters is achieved. If we examine the Silhouette score, we see that the highest value corresponds to 1 cluster in both cases, providing no meaningful information for our study. We assume that the algorithm is unable to identify a well-defined number of clusters because the arrangement of the data is not separated and is dense. In this case, the KMeans Clustering algorithm could be more appropriate.

8.2 K-Means Clustering

K-Means is an unsupervised learning algorithm that aims to group observations in a dataset into different clusters. Since our goal is to identify the different groups to which customers belong, we will try to find the number of clusters that best fits our data.

8.2.1 Hyperparametrization

We will model with the data in logarithmic scaling and without scaling, choosing the one that yields a more coherent result.

- With Log Scaled:

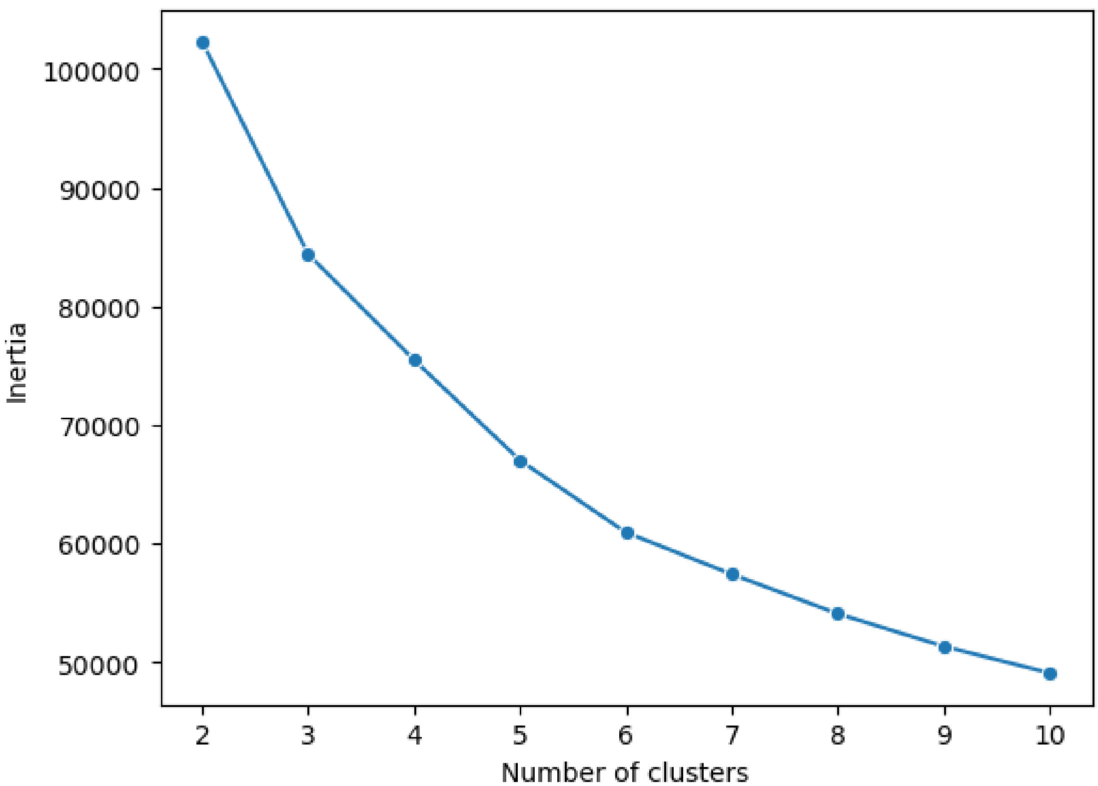
We use the elbow method to find the optimal number of clusters. Plotting the inertia values in a simple line graph with the k values along the x-axis, we could see an "elbow", which is usually the part of the curve with the sharpest angle.

The inertia of the model is the distance of each point from the center of the clusters, the higher the inertia, the greater the distance between the cluster centers and the points.

Because we don't know how many clusters exist in the data, lets start by fitting K-means and examining the inertia values for different values of k.

[56]:
```
num_clusters = [i for i in range(2, 11)]

Inertia_log = kmeans_inertia(num_clusters, df_processed_log_scaled)
```

[57]:
```
plot = sns.lineplot(x=num_clusters, y=Inertia_log, marker = 'o')
plot.set_xlabel("Number of clusters");
plot.set_ylabel("Inertia");
```

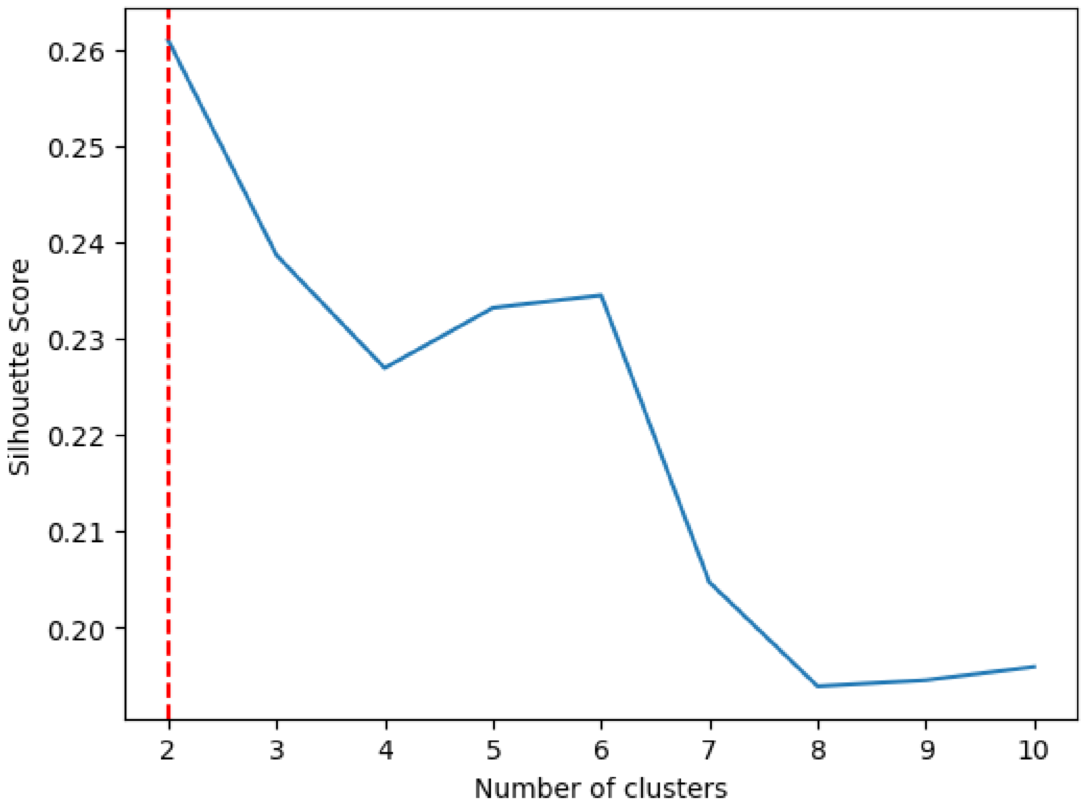


It's not clear where the elbow is but it seems to be in two or three clusters. Let's check the Silhouette score.

Silhouette score provide insights as to what the optimal value for k should be, and uses both intracluster and intercluster measurements in its calculations.

[58]:
```
sil_scores_log = kmeans_sil(num_clusters,df_processed_log_scaled)
```

[59]:
```
plot = sns.lineplot(x=num_clusters, y=sil_scores_log)
plot.axvline(x=2, color='red', linestyle='--')
plot.set_xlabel("Number of clusters");
plot.set_ylabel("Silhouette Score");
```



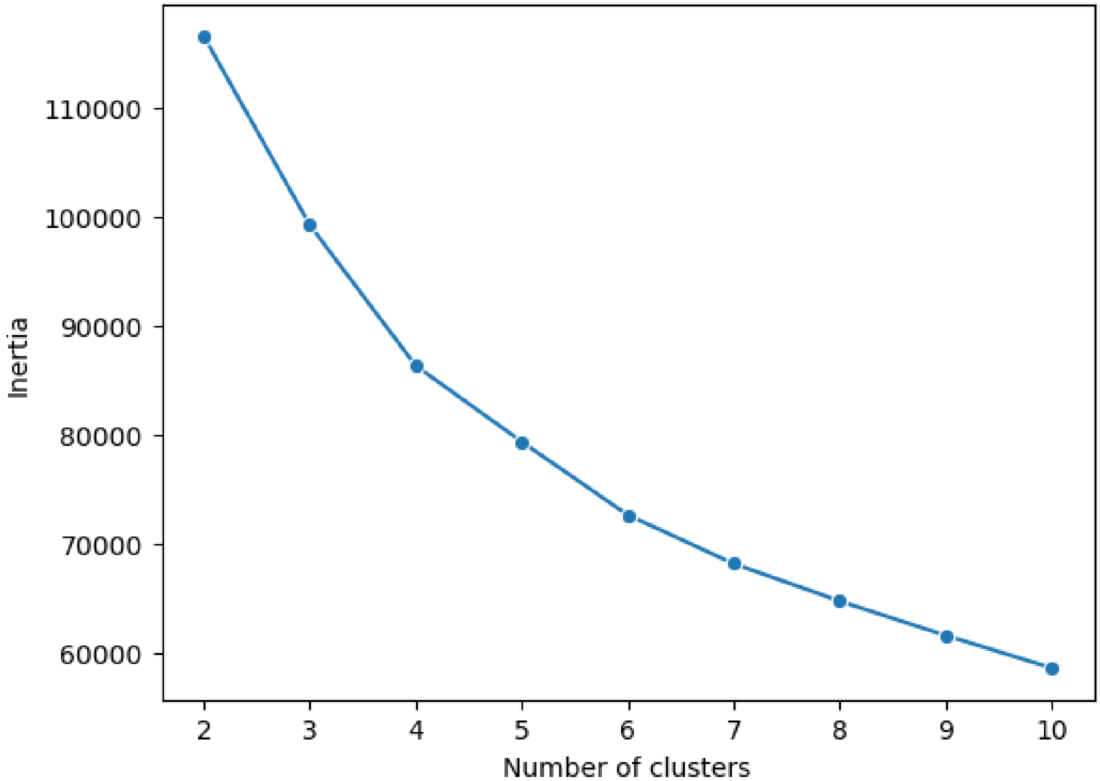
This plot indicates that the silhouette score is closest to 1 when our data is partitioned into two clusters.

It seems that the number of clusters could be two.

- Without Log Scaled:

[60]:
```
num_clusters = [i for i in range(2, 11)]

Inertia = kmeans_inertia(num_clusters, df_processed_scaled)
```

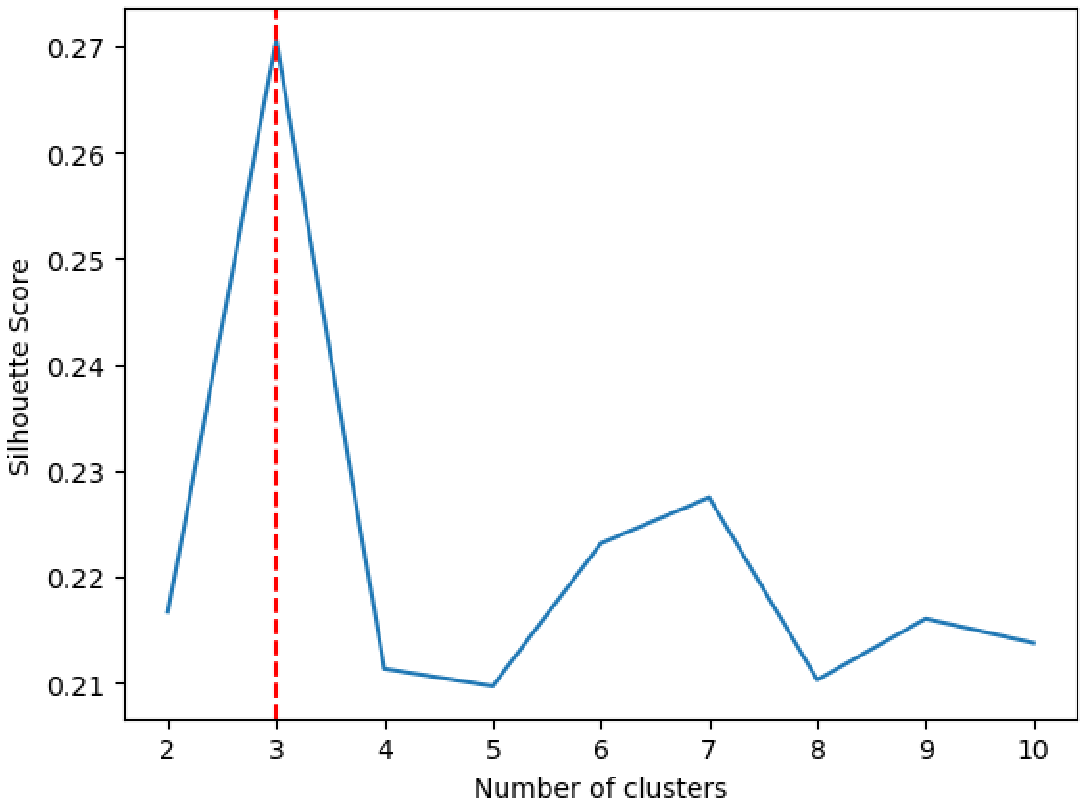
[61]:
```
plot = sns.lineplot(x=num_clusters, y=Inertia, marker = 'o')
plot.set_xlabel("Number of clusters");
plot.set_ylabel("Inertia");
```



It's not clear where the elbow is but it seems to be between three and five clusters. Let's check the Silhouette score.

[62]:
```
sil_scores = kmeans_sil(num_clusters,df_processed_scaled)
```

[63]:
```
plot = sns.lineplot(x=num_clusters, y=sil_scores)
plot.axvline(x=3, color='red', linestyle='--')
plot.set_xlabel("Number of clusters");
plot.set_ylabel("Silhouette Score");
```



This plot indicates that the silhouette score is closest to 1 when our data is partitioned into three clusters.

At this point, it seems that the number of clusters could be three.

8.2.2 Results

Of the two results, we find the one obtained with unscaled data more accurate. It has lower inertia and a higher Silhouette.

Let's instantiate a new K-means model with 3 clusters and fit it to our data and analyze each of the obtained customer groups.

[38]:
```
KMeans_3 = KMeans(n_clusters=3, random_state=42)
KMeans_3.fit(df_processed_scaled)
```

[38]:
```
KMeans(n_clusters=3, random_state=42)
```

- Centers information

[39]:
```
df_centroides  = pd.DataFrame(data = KMeans_3.cluster_centers_, columns =␣
  ↪df_processed.columns)
df_centroides
```

[39]:
```
    balance  balance_frequency  purchases  oneoff_purchases  \
0  0.293041           0.427129   1.505188          1.250992
1  1.179360           0.332818  -0.275974         -0.198171
2 -0.370099          -0.175538  -0.238240         -0.206196

   installments_purchases  cash_advance  purchases_frequency  \
0                1.259218     -0.279275             1.139123
1               -0.288394      1.410342            -0.607785
2               -0.184208     -0.312604            -0.075571

   oneoff_purchases_frequency  purchases_installments_frequency  \
0                    1.523509                          0.962927
1                   -0.302541                         -0.517283
2                   -0.235047                         -0.062961

   cash_advance_frequency  cash_advance_trx  purchases_trx  credit_limit  \
0               -0.386375         -0.308061       1.654555      0.861363
1                1.545513          1.472316      -0.349176      0.606476
2               -0.325983         -0.322932      -0.249854     -0.337011

   payments  minimum_payments  prc_full_payment
0  0.929074          0.231712          0.490872
1  0.521960          0.813179         -0.417449
2 -0.328800         -0.261308          0.008268
```

- Reversing the scaling process

[40]:
```python
df_centroides =  pd.DataFrame(data = scaler.inverse_transform(df_centroides),
 ↪columns = df_centroides.columns)
df_centroides.index.name = "cluster"
df_centroides
```

[40]:
```
             balance  balance_frequency    purchases  oneoff_purchases  \
cluster
0        2195.042867           0.981737  4254.674239       2693.343511
1        4042.220866           0.961275   422.489707        270.003397
2         812.994182           0.850979   503.675947        256.584608

         installments_purchases  cash_advance  purchases_frequency  \
cluster
0                   1561.816165    412.459772             0.948716
1                    152.550986   3808.533674             0.247653
2                    247.422829    345.469247             0.461239

         oneoff_purchases_frequency  purchases_installments_frequency  \
cluster
0                          0.661886                          0.746661
1                          0.114687                          0.158480
```

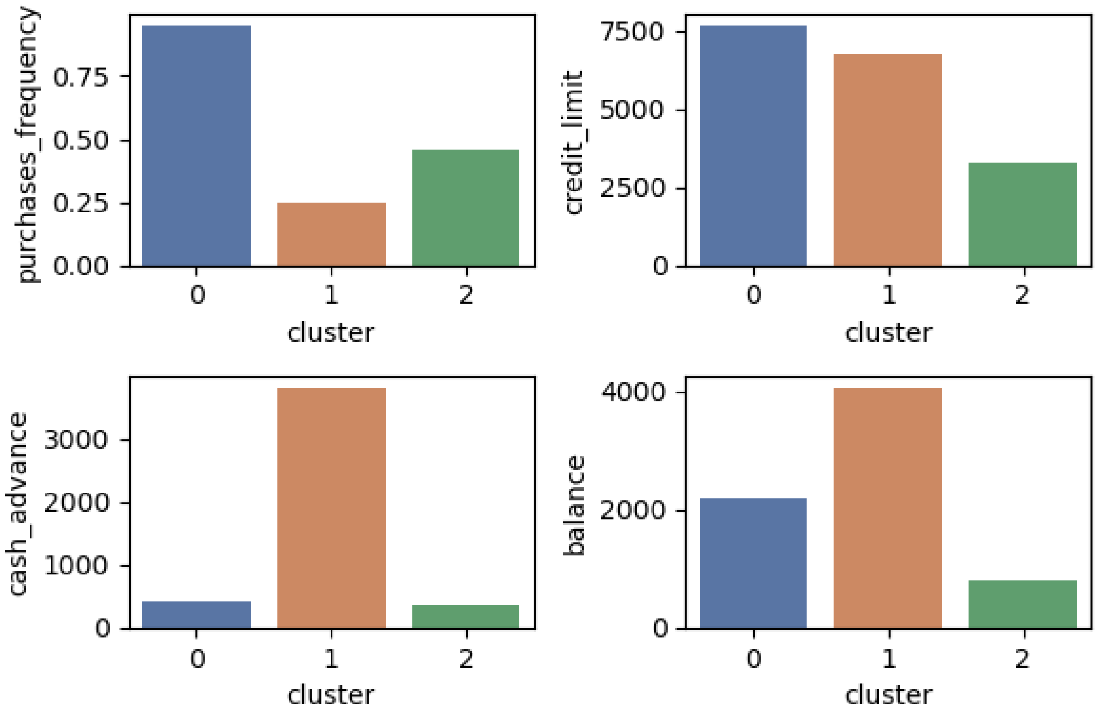
```
2                          0.134912                          0.339011

         cash_advance_frequency  cash_advance_trx  purchases_trx  \
cluster
0                      0.059065          1.336570      56.238673
1                      0.438523         11.860687       6.120229
2                      0.070927          1.248664       8.604542

         credit_limit     payments  minimum_payments  prc_full_payment
cluster
0         7648.543689  3790.903663        905.710893          0.299753
1         6719.404927  2863.687942       1467.229349          0.032889
2         3280.114159   926.051455        429.604555          0.157964
```

[41]:

```
df_processed_grouped = df_processed.copy()
df_processed_grouped["cluster"] = KMeans_3.labels_
```

[154]:

```
key_columns = ["purchases_frequency", "credit_limit", "cash_advance", "balance"]

fig, axes =  plt.subplots(2, 2, figsize = (6, 4))
axes = axes.flatten()

for idx, col in enumerate(key_columns):
    sns.barplot(df_processed_grouped.groupby(by= "cluster")[col].mean(),␣
 ↪palette= "deep", ax= axes[idx])

plt.tight_layout()
plt.show()
```



From the results obtained, we can observe notable differences between the groups:

- **Cluster 0**

  is composed of customers who make a significant number of **purchases frequently** and, at the same time, have the **highest credit limit**.

- **Cluster 1**

  is mainly formed by customers who **use cash advances** on their credit card, probably to address immediate payments, as they present the **lowest purchase frequency**. Therefore, we assume their primary use is for these purposes.

- **Cluster 2**

  is characterized by having the **lowest credit limit**, a **low account balance**, and **occasional purchases**.

Let's represent the arrangement of the clusters and their centroids by reducing the dimensionality of our data using Principal Component Analysis (PCA):

[109]:
```
cluster_client = df_processed_grouped[["cluster", "cust_id"]]
pca_df = df_processed_grouped.drop(["cluster", "cust_id"], axis = 1)
```

[110]:
```
pca = PCA(n_components = 2)
pca_df = pd.DataFrame(pca.fit_transform(pca_df))
```

[111]:
```
KMeans_3pca = KMeans(n_clusters=3, random_state=42)
KMeans_3pca.fit(pca_df)
```

[111]:
```
KMeans(n_clusters=3, random_state=42)
```

[149]:
```
pca_df['cluster'] = KMeans_3pca.labels_

centroids = KMeans_3pca.cluster_centers_

centroids_comp_1 = centroids[:,0]
centroids_comp_2 = centroids[:,1]

plt.figure(figsize=(8,6))
# Component points
data_points = sns.scatterplot(data= pca_df, x= 1, y= 0, hue= 'cluster',␣
↪palette= "deep")
plt.xlim((-40000, 50000))
data_points.set(xlabel='PCA component 1', ylabel='PCA component 2')

# Cluster center
clusters = sns.scatterplot(x= centroids_comp_2, y= centroids_comp_1, marker=␣
↪'X', c= ['black'], s=150)

plt.title("Distribution of clusters")
plt.legend(title='Cluster', fontsize= "large")
plt.show()
```

Distribution of clusters
Cluster
0
1
2
PCA component 2
40000
30000
20000
10000
0
PCA component 1
−40000
−30000
−20000
−10000
0
10000
20000
30000
40000
50000